SWOT-PEST Model for Rural Sports Development Path Transformation in the New Period

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Objectives: At present, China's rural development has entered a new era, and rural sports development is in its infancy. In order to achieve further development in rural sports, it is necessary to clarify the overall environment for the development of rural sports, understand the current stage of rural sports development, and supplement sufficient talents. Methods: Based on this paper, the SWOT-PEST model of rural sports development path transformation in the new era is analyzed, mainly from the perspective of talent big data. Results: A talent big data recommendation system is constructed based on collaborative filtering, the current rural sports development analyzed. Conclusion: The development environment and advantages and disadvantages of the module of talents are in order to facilitate the industry to adopt corresponding strategies.

Key words: new period; rural sports; path transformation; swot-pest model
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Since the beginning of the new century, with the continuous development of the sports industry, more and more high-tech sports products have been born, which has changed our lives while self-innovation, covering all aspects related to us [1]. However, China's rural sports industry, as a large category of sports industry, has little effect in the new era [2]. According to the sixth national census, the rural population accounts for 50.32% of the country's total population, and the urban population accounts for 49.68%. The development of the rural sports industry in China's sports industry is the evidence [3]. With the continuous improvement of human civilization, the sports population is also increasing, people are more aware of the importance of healthy living, and constantly pursue the balance between work and life [4]. Sports is accepted as an irreplaceable factor by more people. More and more urban residents are organizing sports after a meal or on holidays. On the contrary, the lack of rural sports and sports industry population leads to rural sports and rural sports. The industry is stagnant [5]. So how to develop the rural sports industry and the rural economic growth has become an important issue in the context of the country's vigorous development of the sports industry [6]. Based on this, the transformation of rural sports development path in the new era from the perspective of talent development is studied.

From the end of the 20th century to the beginning of the 21st century, the great banner of reform and opening up was held high and a socialist market economy was developed, which made China's economy make a breakthrough [7]. However, in order to further realize the last step in the “three-step”, by the middle of the 21st century, there is still a long way to go to achieve basic modernization [8]. As a weak link in China's economy, the rural economy is both a historical reason and a reality that we have to face [9]. At this stage, in the vast rural areas of China, the main focus is on agricultural production, and the development of rural areas in various regions is very uneven. Although China's rural population accounts for one-half of the total population, farmers' purchasing power is due to backward rural economy [10]. Especially in rural areas in some poor areas, the demand for sports is limited to the government's quantitative and qualitative government projects. The rural population's understanding of sports has not reached the height that the country hopes to achieve, so the rural sports industry is also developing slowly [11]. Therefore, it is inevitable to integrate the development of rural sports industry and rural sports into the new socialist countryside proposed by the Fifth Plenary Session of the 16th CPC Central Committee, closely follow the national policy vane, and promote the rural sports and rural sports industry with the rural economy development [12].

METHODS

Analysis of the Current Situation of Rural Sports Industry Development

Based on the analysis of the current development of rural sports industry in China, a recommendation system is constructed for rural sports development talents. Based on SWOT and PEST theory, the model of rural sports development path transformation in the new era is summarized. The 18th National Congress of the Communist Party of China clearly stated that China should follow the new development path of urbanization with Chinese characteristics. The two sessions clearly pointed out that the core of new urbanization was people-oriented and must protect the fundamental interests of farmers. The new type of urbanization is urbanization based on urban and rural integration, urban and rural integration, production and city interaction, economic intensive, ecologically livable and harmonious development; it is the coordinated development of large, medium and small cities, small towns and new rural communities, and mutual promotion urbanization; its core lies in not paying attention to agriculture and food, ecology and the environment, focusing on farmers, covering rural areas, realizing the integration of urban and rural infrastructure and the equalization of public services, and promoting the overall development of the economy and society; its ultimate goal is to improve the living environment of farmers in an all-round way and improve the quality of life of farmers. With the acceleration of new urbanization, rural sports have many opportunities in the process of development, but they still face many problems, such as the unsound rural sports organization, the low rural sports population, the lack of rural sports facilities, and the peasant sports. The concept is backward, the rural public sports service system is imperfect, and the rural social sports instructors are seriously lacking. Therefore, based on the SWOT-PEST model, the rural sports development strategy matrix analysis table proposed by Zhu Jiaxin is used to comprehensively and systematically analyze the internal development of rural sports. The environment and macro environment are very important for the path selection of rural sports development. The SWOT-PEST model analysis of rural sports development is shown in Table 1.

Table 1
SWOT-PEST model analysis of rural sports development

SWOT-PEST	S (advantage)	W (disadvantage)	O (opportunity)	T (challenge)
P (Policy)	The process of new urbanization promotes farmers' leisure time and improves their cultural and educational level.	Sports organizations are not perfect, lack of venues and equipment, and lack of social sports instructors.	National policy support, new urbanization, new rural construction, urban and rural co-ordination	The two element structure of urban and rural areas hinders the differentiation of social groups.
E (economy)	Increasing farmers' economic income	Rural economy and urban and rural areas are relatively large.	Allocation of social and economic factors for sports industry in urban and rural areas	Increase in economic income of landless peasants and villagers without agriculture
S (Society)	Unique natural resources and folk sports resources	Rural sports population is low and sports concept is backward.	Optimal allocation of sports resources in urban and rural areas	Aging in rural areas and improving social security
T (Technology)	Rural communications equipment is increasing.	Rural network equipment is imperfect, and the public service system is not perfect.	The combined radiation effect of candle towns	The network system is all over the countryside.

Based on the model analysis, it can be seen that China's rural sports industry is developing rapidly and faces a series of opportunities and challenges. The talent problem is an important issue that restricts the development of China's rural sports industry. Therefore, a rural sports industry talent model will be built below. To achieve the matching of talents and industrial development, talent training strategies in a targeted manner should be proposed.

Collaborative Filtering Recommendation Process for Rural Sports Industry Talent Big Data

Although the job recommendation module of the current rural sports industry talent big data recommendation system adopts the user-based collaborative filtering recommendation algorithm, it has made corresponding improvements to the problems and deficiencies of the algorithm itself. The basic idea of user-based collaborative filtering recommendation is: in the user-item scoring matrix, according to the historical user's historical rating information of an item, a similarity measure is used to calculate the target user and other users of the scoring matrix similarity, the item information that the target user has never touched in the neighbor user set should be found, the item information should be scored and predicted, and finally the items are sorted to the target user according to the predicted score value [13]. The system recommendation and filtering principle and process are as follows:

Figure 1
Principle of System Recommendation Algorithm

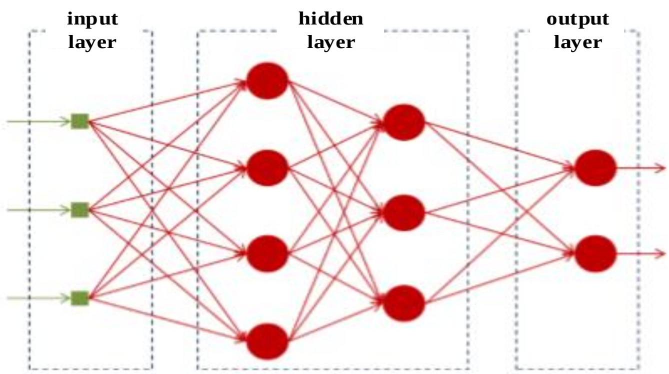
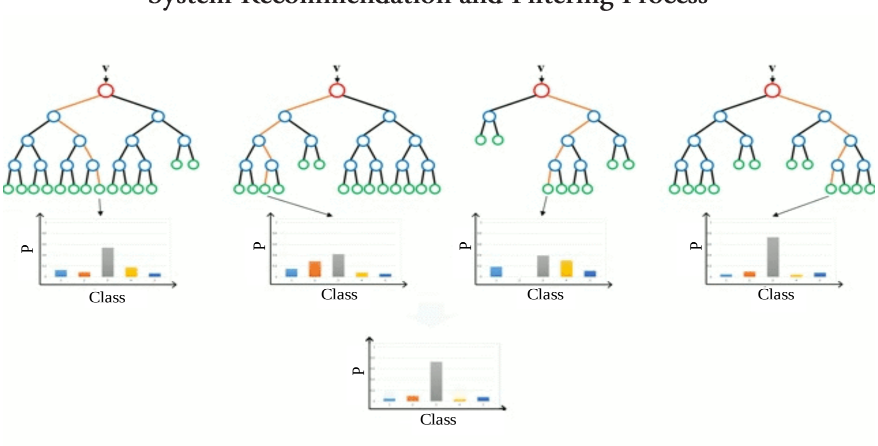


Figure 2
System Recommendation and Filtering Process



In the rural sports industry talent big data recommendation system, the idea and process of the job recommendation function are similar. The system will first collect enough rural sports industry talent data information, and its role is similar to the user-item scoring matrix. When the target user is recommended for the position, the similarity between the target user and other rural sports industry talents is calculated, the similarities are sorted, the similarity users are formed into a neighbor user set, and then the neighbor users are concentrated according to the neighbor users [15]. The job information that the target user has not contacted is used to score the target users, and the job information is sorted according to the predicted score value to form a recommendation result [14]. The core of the recommendation algorithm of the job recommendation module is: In the rural sports industry talent big data recommendation system, when the job recommendation is required to the job seeker X, the system will find other users similar to their social experiences, and then contact those other users. However, the job information that job seeker X has not touched is screened out. Based on these employment information, the system selects the job information that is still valid at the current time and recommends it to job seeker X. This method is based on the user's collaborative filtering algorithm.

In a conventional user-based collaborative filtering recommendation algorithm, the data set can be represented in the form of a two-dimensional matrix $R_{m\times n}$. Among them, $R_{m\times n}$ is the user-item scoring matrix, m represents the number of users participating in the recommendation algorithm, n represents the number of items involved in the recommendation algorithm, and the elements r_{ij} in the matrix represent the user i For the scoring of item j, in the traditional user-based collaborative filtering recommendation algorithm, the value of r_{ij} is generally represented by an integer between 0 and 5, where the number 0 indicates that user i has no scoring information for item j, and the number 5 indicates user i. The evaluation of item j is the highest, and the meanings represented by other values are analogous, indicating the degree of user preference for the item.

Finding the nearest neighbor of the target user is the core part of the algorithm. In the talent big data recommendation system, the quality of the nearest neighbor user and the search rate of the target talent user will directly affect the quality of the job recommendation result. When searching for the nearest neighbor of the target user, the traditional user-based collaborative filtering recommendation algorithm performs a similarity measure between the target user and all other users, and then selects a user with a higher similarity to form a neighbor user set. In the process of finding the nearest neighbor, the system obtains a large number of similarity users, and then sorts these similarities, and selects a certain number of users to form the nearest neighbor user set. There are two main ways to determine the number of users in the nearest neighbor user. First, when the system calculates the neighbor user, the user sets the number of neighb ors required in advance, that is, the number of neighbor users is determined. This method can easily control the number of neighbor user sets, and is simpler to design and has a wider application range. However, the disadvantage is that some users with similar degrees of similarity may be added to the neighbor user set by the system. This method is also used in the talent big data recommendation system, because in the case of enough talent information, it can effectively avoid its shortcomings. Second, before the system calculates the similarity of the user, the user first presets the threshold range of similarity. When the system calculates the similarity between the target user and other users, only the similarity value is within the preset threshold range. This user can be added to the neighbor user set. In this way, it is ensured that the users of the neighbor users are highly similar to the target users. Common methods are used in the calculation of similarity: cosine similarity, improved cosine similarity, Pearson correlation coefficient, Euclidean similarity.

Improvement Measures Based on User-Based Collaborative Filtering Algorithm

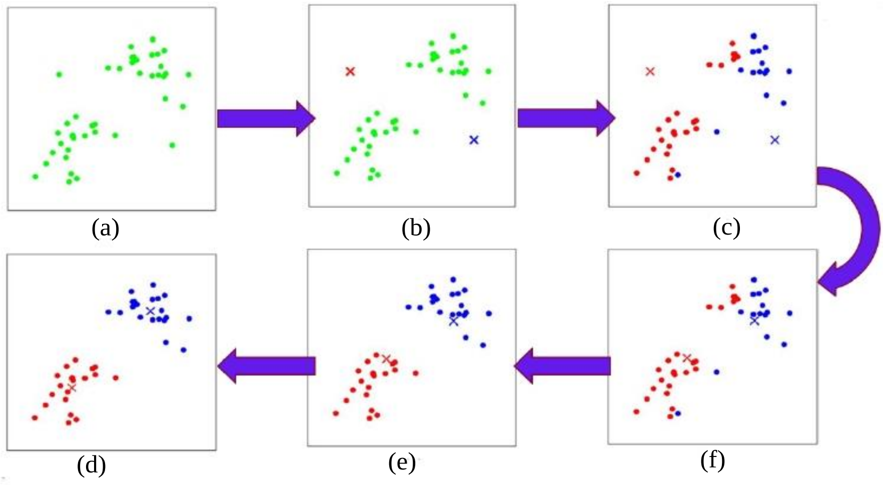
Aiming at the cold start problem caused by the collaborative filtering recommendation algorithm over-reliance on the scoring matrix, two similarity component weighting calculation methods are used in the talent big data recommendation system to calculate the similarity. The first is based on the talent information entered by the talent users. The calculation of talent feature similarity, the second is based on the user-enterprise scoring matrix recorded by the system to calculate the similarity of employed talents. When using the weighted calculation to calculate the similarity, even if the target user is a user without any work experience, the system can calculate the talent similarity based on the skill type, skill ability value and other information that the user enters the system. According to the talent feature similarity, the target user can also find the nearest neighbor user set, so as to complete the recommendation of the target user recruitment information. For users with rich social experience and relatively perfect work information, the system will calculate two similarities when there is information about the talent in the talent information database and the talent-enterprise information database. In this way, the cold start problem of not being able to recommend a job for a user with incomplete information can be well solved.

In the calculation of two similarity components, the calculation of the similarity component simY of the employed talent is calculated by using the modified cosine similarity in the traditional collaborative filtering recommendation algorithm, while the talent feature similarity component simX utilizes the talent ability defined in this paper. The distance is calculated, and the design idea of the formula will be mainly introduced below. In the talent big data recommendation system, when the user enters the skill information that he is good at in the system, the system makes a more detailed specification, that is, the user needs to explain which exercises the skill has experienced, and the ability to improve the skill. The quantity is represented by a numerical value. For example, when the user enters the Java in the programming language, the user needs to indicate what project he has participated in in the language, and the Java language proficiency is improved in the process of participating in the project, expressed with a clear numerical value. Therefore, after the user perfects his or her own information, the system will get a numerical talent feature information, such as (Java, 2), indicating that the user's Java ability value is 2, thus forming a "talent-skill" matrix.

RESULTS

On the above experimental data set, the traditional user-based collaborative filtering algorithm and the improved user-based collaborative filtering algorithm are compared. The data collected in this paper has been normalized and clustered. The process is as follows:

Figure 3
Data Processing Flow



The following is the clustering of some data:

Figure 4
Clustering of Partial Data

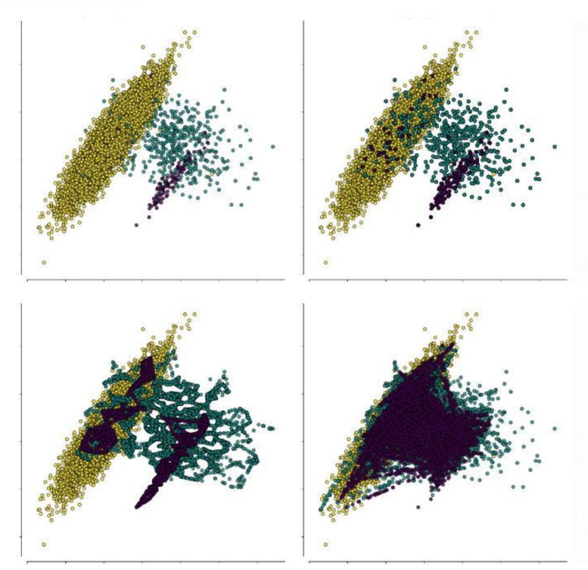
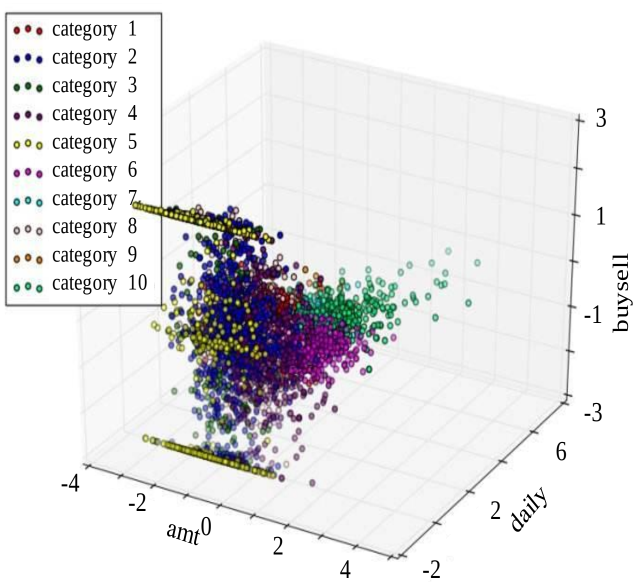


Figure 5
Clustering Tool



The number of nearest neighbors of the selected target users is from 10 to 50, and the interval is 10. The average value of the MAE values is taken as the result of the final experiment. There are four experiments in this paper: Experiment 1 is, in the user-enterprise scoring matrix, running the traditional user-based collaborative filtering algorithm to obtain its MAE value as a comparative experiment of the improved algorithm; Experiment 2 is that in order to determine the value of α, different values of α in the rural sports industry talent data set are selected to improve based on the user's collaborative filtering algorithm compares the value of MAE and determines the value of α. In experiment 3, after determining the value of α, the algorithm is operated by the weighted similarity calculation method, that is, only the similarity calculation method in the traditional algorithm is changed. Obtain the MAE value and compare it with the experimental results of Experiment 1. Observe whether the weighted similarity will affect the recommended quality. Experiment 4 is that after determining the value of α, the improved one is based on the rural sports industry talent data set. The user's collaborative filtering recommendation algorithm obtains the MAE value and compares it with the experimental results of Experiment 3. Observe whether the use of cluster-based nearest neighbor lookups will have an impact on the quality of recommendations.

In the first experiment, the traditional user-based collaborative filtering algorithm is run in the user-enterprise scoring matrix, that is, the modified cosine similarity is used to measure the similarity between the target user and other users in the matrix, and 10, 20, 30, 40, 50 are selected respectively. As the nearest neighbors constitute the neighbor user set, the score prediction produces the recommendation result, and the average absolute error is used to evaluate the recommendation result. In the second experiment, in order to determine the value of α, different values of α are selected (α=0, 0.1) , 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1), different nearest neighbors k are selected(k = 10, 20, 30, 40, 50) after the improvement of the rural sports industry talent data set User-based collaborative filtering algorithm, compare the value of MAE, determine a relatively accurate range of α, then select α to two decimal places, perform experiments again, compare the values of MAE, and finally obtain a relatively accurate α Value. That is to say, this experiment uses the parallelization calculation of the collaborative filtering recommendation algorithm to generate the recommendation results. Firstly, the rural sports industry talent characteristic information is clustered, and then the target user belongs to the class, and the weighted similarity is calculated in the class. The difference in the number of nearest neighbors formed constitutes a set of neighbor users, and a recommendation result is generated. The MAE valuesobtained in Experiment 2 are shown in Table 2.

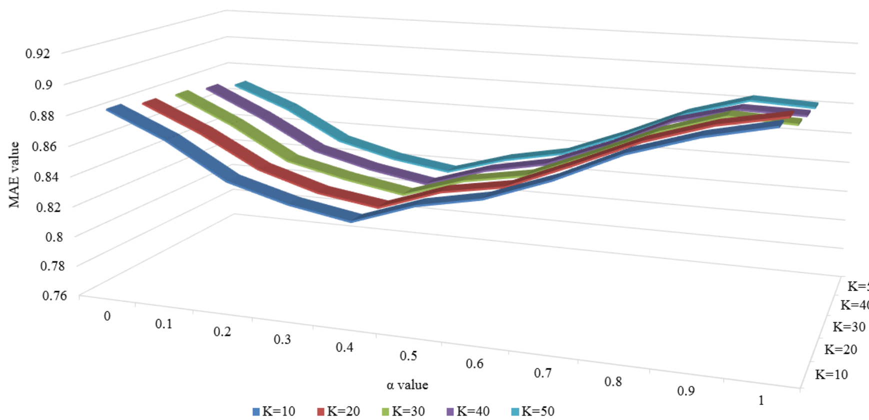
Table 2
Selects the MAE Value of Different Alpha Values.

α MAE	K=10	K=20	K=30	K=40	K=50
0.0	0.883	0.879	0.877	0.874	0.869
0.1	0.866	0.862	0.859	0.856	0.854
0.2	0.843	0.841	0.837	0.835	0.833
0.3	0.832	0.829	0.828	0.825	0.823
0.4	0.825	0.823	0.821	0.818	0.817
0.5	0.839	0.837	0.834	0.831	0.829
0.6	0.847	0.844	0.841	0.839	0.837
0.7	0.862	0.861	0.858	0.855	0.853
0.8	0.881	0.879	0.876	0.874	0.871
0.9	0.894	0.892	0.889	0.885	0.883
1.0	0.903	0.900	0.887	0.884	0.881

In order to facilitate the observation of the data in Table 1, the data in the table is displayed in the form of a line graph, as shown in Figure 6, the same alpha value is known from the figure, and the MAE value is selected with k, which increases and becomes smaller; under the same k value, there is an α (0.3 < α < 0.5), so that the value of

MAE is the smallest.

Figure 6
The Comparison of the MAE Value of Collaborative Filtering Algorithm with Different Alpha Values



Therefore, in the experiment of determining the value of α next, k=10 is set to be constant, first the value of α from is selected [0.35, 0.45], and the change of MAE value is based on the change of α value according to the experiment regularity. From which it can be determined that when the value of α is accurate to two decimal places, the optimal value is 0.37.

In the third experiment, after determining the value of α, in order to determine whether the calculation method of the weighted similarity mentioned in this paper will affect the recommendation quality, and the similarity calculation method is used as the variable, the similarity measure of the weighted similarity is used in this experiment. The method replaces the traditional similarity measure method for experiment. Figure.7 is the data processing tool in the experiment. In this paper, the experimental results are compared with the experiment one, and the result of experiment three is compared with the result of experiment one, as shown in Fig.7. Among them, the only variable of experiment 1 and experiment 3 is different in the calculation method of similarity. Experiment 3 uses the calculation method of weighted similarity proposed in this paper. In the case of the same k value, the MAE value of experiment 3 is smaller. It is indicated that the recommendation result is more accurate, that is, the calculation method using weighted similarity can improve the recommendation quality of the system.

Figure 7
Data Classification and Processing Tools

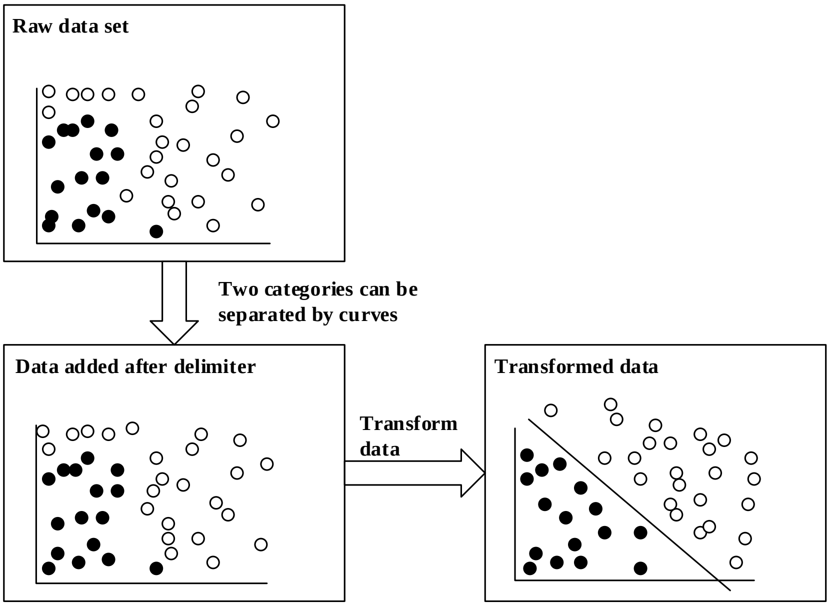
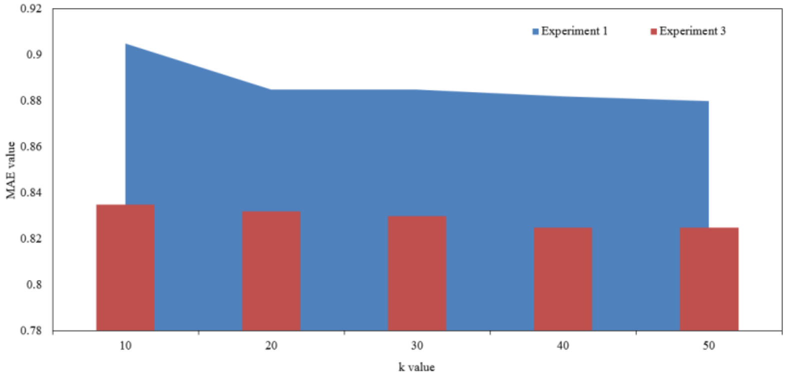
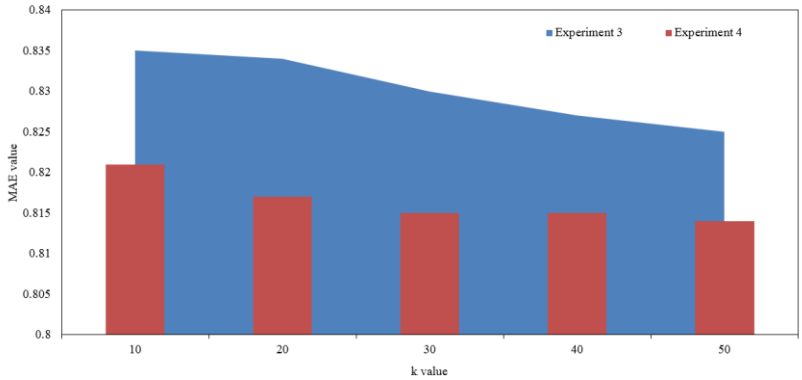


Figure 8
Comparison between Experiment Three and Experiment 1



In the fourth experiment, in order to determine whether the cluster-based nearest neighbor search proposed in this paper can improve the recommendation quality, in addition to the weighted similarity calculation method, this experiment also using the cluster-based nearest neighbor search to calculate the neighbor user. The difference from Experiment 3 is whether to use cluster-based nearest neighbor lookup. The results of Experiment 4 with the results of Experiment 3 are compared, as shown in the following figure:

Figure 9
Comparison between Experiment Three and Experiment four



Among them, the displacement variables of Experiment 4 and Experiment 3 are whether to use cluster-based nearest neighbor search, that is, Experiment 4 uses the cluster-based nearest neighbor lookup based on the weighted similarity, which can be seen from Fig. 9 that the MAE value of Experiment 4 is relatively small when the k values are the same, indicating that the recommended results are more accurate than the experimental three-phase, that is, cluster-based nearest neighbor lookup is used based on the weighted similarity. The neighbor user calculation method can improve the recommendation quality of the system.

DISCUSSION

At present, China's rural economy is developing rapidly, and the development of various industries is in full swing. The rural sports industry has also gradually developed. However, in the process of industrial development, it also faces a series of opportunities and challenges. The talent problem is the current rural sports industry, which are important issues of development. Therefore, talent recommendation, matching and training are focused on, the current recommendation process and shortcomings of user-based collaborative filtering algorithms is analyzed, and improvements are proposed based on user-based collaborative filtering algorithm: computational weighted similarity degree, cluster-based nearest neighb
neighb
or lookup and collaborative filtering recommendation algorithm parallelization. A comparison experiment is designed to verify and analyze the improved user-based collaborative filtering recommendation algorithm. It can be seen from the experiment that the collaborative filtering recommendation algorithm based on weighted similarity calculation and cluster-based nearest neighbor user search is more suitable for the rural sports industry talent big data recommendation system, which can improve the accuracy of job recommendation.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

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